

Finding Balance in Generative Product Design

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Abstract

Generative design develops complex forms and structures similar to those found in nature, taking advantage of automated tasks and high-scale computing power. This approach benefits designers in the creation systems that are efficient, resilient and visually engaging. These systems follow specific rules for form generation and meet clear design goals in terms of shape, strength, mass, and other physical attributes.

There is a large number of methods for creating generative systems, based on establishing desired outcomes and behaviors for how components relate to each other. Examples of methods include L-Systems, Shape Grammars, Swarm Intelligence, Form Optimization, Lattice Design, and many others. From a designer's point of view, most of the approaches fall into two categories: by subtraction and addition. In a subtractive process, objects are analyzed based on specific targets for strength, mass or similar attributes, and any sections that are unnecessary to satisfy them are removed. An additive approach predefines design goals and constraints for a given problem and generates large number of iterations of potential solutions that meet such goals. Subtractive processes have relatively small learning curves but they tend to offer only incremental improvements over current solutions. Additive processes provide more benefits and flexibility for form generation and automation of processes but their steep learning curve makes them hard to use, discouraging designers without adequate knowledge on mathematics and programming.

While the use of any of these two approaches provides great potential for design development, it is common for designers to pick one of the two approaches early in their development process and not make an effort to include the other approach along the way. The combination of subtractive and additive methods, however, can lead to solutions that are more effective and cohesive. This paper discusses an integrated method based on iterative design processes where designers refine their concepts multiple times, achieving higher levels of success. This integrated, iterative process puts designers at the center of the process, providing tools with varied benefits and levels of complexity, that maximize automation and computational processing power.

Keywords: *Generative design, product design, industrial design, automation, additive manufacturing*

1 Introduction

Generative design is becoming a key component in the creation of new human-made products, systems and environments. Based on how natural systems develop shapes in complex patterns, generative design is a process that includes three key components: a set of rules or schema, a way for variations to develop, and specific outcomes that the variations need to meet (Krish, 2011). When applying these key components to product design it is possible to see various benefits. First is the development of design solutions that are efficient, resilient and aligned with natural eco-systems. Second is the use of digital technology and algorithms in order to create large amounts of feasible design directions. Third is the creation of forms and patterns that are attractive and dynamic.

There are multiple ways of applying generative design into the development process and from a designer's point of view, most of the approaches fall into two general areas: by subtraction and by addition. In a subtractive process, parts of an object are analyzed based on their strength or durability in order to remove unnecessary sections while maintaining performance. This approach is achieved with methods such as shape optimization, trabecular structures and lattice design (Autodesk, 2018; Singh, 2012). A subtractive approach has a relatively small learning curve but it also derives from designs that were over-defined and provides only incremental improvements over current solutions. An additive approach takes design goals and constraints for a given problem and generates large amounts of potential solutions that meet such criteria. Methods for additive generative design are abundant and include L-systems, shape grammars and tabernacle structures, to name a few. While the automatic generation of alternatives is impressive and goes beyond what human capacity could produce by itself (Cui & Tang, 2012), it also makes it overwhelming to create algorithms that work in an expected manner, not to mention having to select solutions that viable and desirable among so many choices generated.

A common misconception when looking at these two approaches is that designers need to select the one that is more appropriate for their needs. A single-direction approach provides good results but it is also limited and might not address all aspects relevant to a new design in order to be successful when implemented. An integrated method based on iterative design processes is proposed, where designers refine their concepts multiple times, achieving higher levels of success. An iterative process that goes between additive and subtractive workflows leads to solutions with the right balance of shape formation and optimization.

At the core of this process is the role of the designer, who collaborates with computers in creating systems that are complex, interconnected, resilient, and novel (McCorkmack, Dorin & Innocent, 2004). The connection between generative design and iterative design process provides a innovative platform in which designers can feel comfortable using familiar workflows and combine them with next-generation technology, all leading to more efficient and engaging designs.

2 Influence of generative design

Generative design has been an important tool in design since the 1970's. It was originally adopted in computer science and then in Architecture, Engineering and Construction (AEC) industries. In recent years it has become popular in other design disciplines, such as product, visual communication and user experience. Generative design takes advantage of the

computer's power in a way that mimics nature's evolutionary process (Frazer, et al., 2002). The result are designs that are spatially novel, efficient and manufacturable (Shea, et al., 2005).

The core benefit of generative design lies in automation and can be understood from two angles: processes and form generation. On one hand is the automation of repetitive processes, which is perhaps the most important benefit of generative design (Castro, 2012). AEC is an ideal scenario for applying automated processes where the planning construction of large buildings that require multiple systems working together. Large scale projects such as buildings, bridges and urban infrastructure require repetitive implementation of similar components such as doors, windows, plumbing, electrical outlets, framing structures, lighting, etc.

The other way in which generative design is beneficial for design process is the creation of forms that mimic nature. By using algorithms that follow basic, progressive rules as components are created it is possible to develop structures that are complex, intricate, and that have a naturally fluid and efficient. Designers look for ways of creating nature-inspired forms due to their unique appearance, intricate detail, and strongly positive reaction in consumers (Huang & Li, 2014).

The connection between generative development is not limited to the potential solutions that are generated but also to the processes in which these iterations happen. The ability to generate multiple alternatives that potentially solve a problem align directly with how designers are trained. Design process is heavily based on ideation and iteration. Good designs don't come from a single, perfect solution, but rather from a large number of initial ideas that were analyzed, developed and selected, in order to find the best direction. In many cases "it may require generating 100 ideas (many of them mediocre) in order to come up with three truly inspirational solutions" (IDEO, 2011). This process focuses initially on "quantity" in order to guarantee that several ways of solving a problem have been considered. From there the focus transitions to "quality" where the ideas with potential are selected and refined. The process of generating multiple ideas and refining them over and over again is all about automation, which makes it a perfect environment for using generative design tools. Under this scenario, using a computer as a tool simply for automation results very limited. With generative design, designers benefit from automation and they can also be inspired by it, letting their creativity go in ways previously unimaginable (Janssen, et al., 2002). Generative systems end up freeing up designers from traditional frameworks for problem-solving. Instead of being forced to reduce alternatives as a concept is being developed, they can use generative methods to expand their exploration and to include complex systems and variables (Louishidha, 2014). This is a safe way of opening up ideas as computers will remain true to their parameters, avoiding digression from the original goals set for a design problem. No matter which angle provides the incentive for integrating generative design processes, it is necessary to establish the goals that want to be met for a design problem as well as the parameters and tools that will be used for testing. The beauty of generative design comes in letting computers generate large number of solutions that connect parameters with goals in varied and unexpected ways.

3 Generative design's Impact in product development

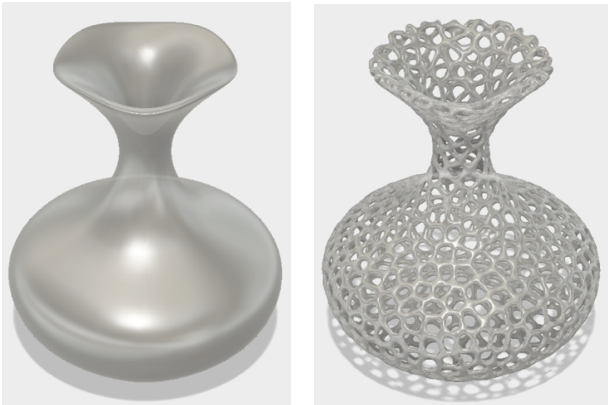

As previously discussed, one of the most visible benefits of generative design is the ability to emulate forms that come from nature. The key when doing this is that designers use generative systems to go beyond just visual appearance. Just as nature doesn't create forms that simply "complex" or "pretty" true generative design creates forms that are intrinsically efficient. In

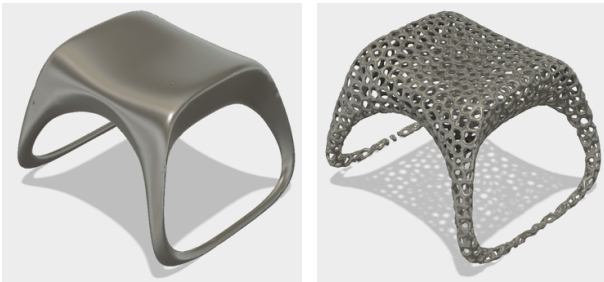
case of spatial patterns, they reflect levels of solving physical constraints with superior efficiency, minimizing resources and maximizing structural integrity.

A small experiment to illustrate benefits of generative design was with the use of Voronoi diagrams and 3D printing. Voronoi diagrams are a way of dividing a plane based on the “nearest neighbor rule: each point is associated with the region of the plane closest to it.” (Aurenhammer, 1991). Three basic objects were modeled in CAD and then 3D printed: a vase, a bowling pin and a stool. First they were modeled as solid shapes. Then each object was run through a software tool that applies a Voronoi pattern to its surface and the result is what most people expect from generative design forms: a cored-out structure that is typically seen in corals or the inside of bones. The new versions were 3D printed and both versions are compared in Table 1 in terms of the time it took to print them and how much material they used.

The results of the experiment showed that printing time was not improved with Voronoi-based shapes. For the vase there was a reduction time of 8% but the bowling pin and stool took 19% and 16% longer to print, respectively. The true advantage of the process was in the amount of material used, which was reduced significantly in all three objects: 57% for the vase, 54% for the bowling pin, and 46% for the stool. A strength-test was not performed but a quick inspection of the objects showed similar strength between both versions. While this is not an exhaustive comparison between the objects, it provides an initial idea on areas of opportunity for improvement of resources and performance.

Table 1: Three objects were modelled and 3D printed in two versions: solid and cored out with a Voronoi pattern, in order to understand the impact of printing time and material use.

	<p>Vase</p> <p>Time to print: 316min (Solid) 290min (Voronoi)</p> <p>Material used: 45.7gr (Solid) 19.7gr (Voronoi)</p>
	<p>Bowling Pin</p> <p>Time to print: 116min (Solid) 138min (Voronoi)</p> <p>Material used: 15.8gr (Solid) 7.3gr (Voronoi)</p>

	<p>Stool</p> <p>Time to print: 497min (Solid) 575min (Voronoi)</p> <p>Material used: 78.2gr (Solid) 43gr (Voronoi)</p>
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4 Applying generative systems from two angles

As generative design becomes more prevalent in product design, various methods for its implementation are being used at different stages of the design process. Traditionally there are five common types of generative systems: Shape Grammars, L-Systems, Cellular Automata, Swarm Intelligence, and Generic Algorithms (Singh & Gu, 2012; Krish, 2011; Zimmerman, 2017). These systems are used in multiple applications and cover a wide variety of possibilities for generative form creation. When looking at applications closer to product design and fabrication, software company Autodesk (2018) proposes four types: form synthesis, lattice and surface optimization, topology optimization, and trabecular structures. A cross-analysis of all these different types of generative tools reveals two overarching categories: by subtraction and by addition.

4.1 Subtractive method

An easy way to achieve benefits from generative design is to use a subtractive method. In this scenario, existing objects are analyzed based on specific targets for strength or durability, and any sections that are unnecessary to satisfy them are removed. Generative models that fall in the subtractive category include shape optimization and lattice design. Both of them work with solid shapes, identifying sections of the body that can be removed without compromising its performance. Shape optimization will focus more on specific forces that will affect the piece such as weight loads or torque. Simulation analysis will help to determine which portions of the body are truly necessary to sustain such forces, removing any excess material. Structural frames in vehicles, furniture and mechanical equipment benefit greatly from shape optimization (Figure 1). Lattice design works slightly different, where CAD software will create a mesh pattern that fills the interior of a body, removing substantial material without compromising strength or durability (Panesar et al., 2018). An example of lattice design that has been well accepted in the marketplace are midsoles of athletic shoes (Figure 2). Traditionally made out of solid foam, these shoes incorporate latticed designs that work just as well with less material but offer additional benefits such as different levels of stiffness across the sole, depending on the foot's needs, as well as more options for materials, many of them recyclable.

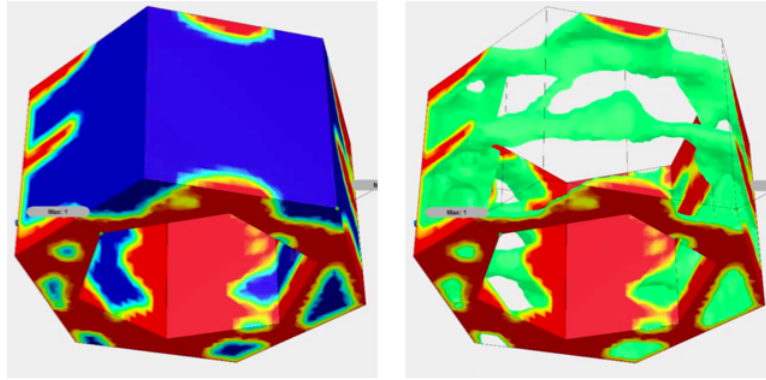


Figure 1: A joint section was analysed with a shape optimization tool based on weight loads against it. The image in the right shows a resulting shape with unnecessary sections removed while still supporting the load.



Figure 2: Photo by DesignMilk. Adidas Futurecraft 3D, a concept running shoe with an intricate 3D printed midsole designed to provide a custom contoured footbed from an in-store scan. CC BY-SA 2.0. <https://www.flickr.com/photos/designmilk/21526243834>

Generative design by subtraction tends to be relatively easy to integrate into any design workflow, given that it doesn't require for designers to change how they develop objects. This subtractive approach, however, is based off components that were designed without particular considerations for shape optimization and provides only incremental improvements for use and cost without transforming how products are envisioned.

4.2 Additive method

A second approach for generative design is with additive processes. In this case, a set of rules and goals are defined, so that any designs coming out from the process are guaranteed to meet specific requirements. This process normally involves the use of complex programming and algorithms, which serve to define parameters. Specific methods for additive processes are more

abundant and include Shape Grammars, L-Systems, Swarm Intelligence, Trabecular Structures and Cellular Automata, among others. In all of these cases, form generation happens out of defining rules for generation of simple shapes that become more complex systems over time or until a goal is reached, providing designers with plenty of space for experimentation and discovery of unexpected results (Attar et al., 2009). As result of the process, large amounts iterations that meet the set criteria are developed by a computer program so that designers can pick the one that is more appropriate for their needs. An exploration from Madeline Gannon uses a basic shape that is model digitally around CAD workspace, leaving a trace of iterations that are connected together to form collars (Figure 3). This process takes some inspiration from Swarm Intelligence, the natural phenomena where flying or swimming animals move together in packs.



Figure 3: 3D Printed collar by Madeline Gannon. CC BY-NC 2.0
<https://www.flickr.com/photos/madelinegannon/12076576784/>

The additive approach takes design goals and constraints for a given problem and generates thousands of potential solutions that meet predetermined criteria. Automation in this case is key to develop large number of solutions for the same problem. While the automatic generation of large amounts of alternatives is impressive and goes beyond what human capacity could produce by itself, it also makes it overwhelming to identify directions that are viable and desirable among so many choices.

5 Integrating additive and subtractive

A single-direction approach for generative design can provide good results but it is also limited and might not address all aspects relevant to a new design in order to be successful when implemented. Many products consist of parts made out of different materials, which are exposed to different types of forces and uses. While some plastic parts could easily be made with additive processes such as 3D printing, wooden parts often need subtractive processes such as machining. In cases like this, combining processes is key in order to optimize each part individually, as well as the product as a whole.

At a deeper level, a proposed integrated method envisions a process that starts with one approach—either additive or subtractive—and then applies a second approach to the result. The

process can be repeated as many times as necessary, becoming an iterative process that provides a solution that is balanced and refined. A good example of integrated generative design is the Elbo chair, designed by Arthur Harsuvanakit and Brittany Presten at Autodesk (Figure 4). The team defined a basic set of rules for a chair, in terms of dimensions, ergonomic points and load capacities. From there, an experimental software named Dreamcatcher generated hundreds of iterations of chairs that met the criteria (Rhodes, 2016). Once the iterations were complete, designers evaluated and found what they considered the best solution. Not satisfied with the level of sophistication of the chair that Dreamcatcher generated, Harsuvanakit and Presten refined the model further with a combination of CAD modeling and shape optimization simulations. The final result has an attractive yet unusual appearance that would have been hard to envision and develop without collaborating with computational tools.



Figure 4: Elbo Chair designed by Autodesk. Photo by Design Milk/Autodesk. CC BY-SA 2.0
<https://www.flickr.com/photos/designmilk/30240388714>

A key benefit of using both approaches, particularly by starting with a subtractive method, is to encourage more designers to adopt generative design and to set them up for success rather than for failure. While subtractive processes are less beneficial in terms of efficiency and reduction, they are considerably easy to use. This means that a designer can integrate these steps without dramatically abandoning familiar methods for product creation. As this process becomes more familiar and beneficial, designers will be likely to integrate more strategies of generative design into their process.

Good design comes from balance, ranging from wants and needs to form and function, and even benefits and cost. Designers often have a challenging task of exploring multiple sides of a design in order to find the sweet spot that will be accepted by users, manufacturers, and other key stakeholders. By using the proposed model for combined generative design, designers benefit from understanding and integrating attributes from different approaches.

6 Conclusions

There are two challenges that designers face when integrating generative tools into their process. First is the need to run programs that require intense mathematical knowledge and programming. Designers' limited training in computer science hinders their ability to create

generative patterns even if from a conceptual sense they would be able to manipulate them and apply them into everyday applications. The second challenge is that the creation of generative iterations offers solutions that work from a technical side, based on rules and goals, but not always take into account elements such as aesthetics, emotional attachment and user experience. The designer's intuition is a key tool for connecting all of these elements together in order to find engaging solutions that benefit from generative approaches.

From a technical standpoint, combining additive and subtractive generative processes offers the potential to reduce gaps in the development of new designs and it also provides designers with more flexibility for how and when they can apply these ideas into their workflows. Designers often have clear expectations of the outcomes of a given design. When used correctly, generative design allows them to obtain solutions that are efficient and resilient in ways inamigable by human cognition alone. Generative tools provide more space for designers to explore potential solutions with the assurance that design goals can be met with any direction that the computer develops. Subtractive methods such as form optimization and lattice design offer a great point of entry for generative tools, as they complement existing designs in later steps of the process rather than changing them from the ground up. While the benefits of subtractive processes are not as radical as with additive ones, they provide a more manageable learning curve and can encourage designers to adopt them more frequently.

No matter which generative tools are applied, they offer the great benefits of automated tasks that would be too complicated or time consuming without help from computers. Additionally, they develop design solutions that are more efficient and aesthetically appealing. Generative design is an exciting path for product design that will continue to develop in years to come. As it becomes more user friendly and easy to integrate into existing design processes, it will improve the way that design solutions are created and how they address real-world needs.

Citations and References

- Attar, R., Aish, R., Stam, J., Brinsmead, D., Tessier, A., Glueck, M., Khan, A. (2009). Physics-based Generative Design. In: Proceedings of the 13th International CAAD Futures Conference. Montreal, Canada.
- Aurenhammer, F. (1991). Voronoi Diagrams: A survey of fundamental geometric data structure. ACM Computing Surveys, 23 (3), 345-405.
- Autodesk, Inc (2018). What is Generative Design. Retrieved on 2 February from <https://www.autodesk.com/solutions/generative-design>
- Castro, G. (2012). TetraScript: A responsive pavilion, from generative design to automation. Architectural Computing, 1 (10), pp. 87-104.
- Cui, J., Tang, M. (2012). Presenting 3D Shape Grammars in a Generative Product Design System. In: Gero, J. (ed) Proceedings of the 5th International Conference on Design Computing and Cognition. 7-9 June, Texas A&M University, USA.
- Frazer, J., Frazer, J., Liu, X., Tang, M., Janssen, P. (2002). Generative and Evolutionary Techniques for Building Envelope Design. In: Soddu, C. (ed) Generative Art 2002: 5th International Generative Art Conference. 11-13 December, Milan, Italy.
- Huang, Y., Li, J. (2014). Generative product design inspired by natural information. In: Yamamoto, S. (ed) 16th International Conference on Human Interface and Management Information. Heraklion, Crete, Greece, 22-27 June.
- IDEO (2011). Human Center Design Toolkit. 2nd Edition. IDEO.org, Palo Alto, California.

- Janssen, P., Frazer, J., Tang, M., (2002). Evolutionary Design Systems and Generative Processes. *Applied Intelligence*, 16, pp. 119-128.
- Krish, S. (2011). A practical generative design method. *Computer Aided Design*, 43, pp. 88-100.
- Louishidha, J., Srivathsan, A. (2014). Generative methods and the design process: A design tool for conceptual settlement planning. *Applied Soft Computing*, 14, pp. 634-652.
- McCormack, J., Dorin, A., Innocent, T. (2004). Generative Design: A paradigm for design research. In Redmond, J. Et al. (eds) *Proceedings of Futureground*, Design Research Society, Melbourne.
- Panesar, A., Abdi, M., Hickman, D., Ashcroft, I. (2018). Strategies for functionally graded lattice structures derived using topology optimisation for Additive Manufacturing. *Additive Manufacturing*, 19, pp. 81-94.
- Rhodes, M. (2016). So, Algorithms are Designing Chairs Now. *Wired Magazine Design*. Accessed on 10 February 2018. <https://www.wired.com/2016/10/elbo-chair-autodesk-algorithm/>
- Shea, K., Aish, R., Gourtovaia, M. (2005). Towards integrated performance-driven generative design tools. *Automation in Construction*, 14, pp. 253-264.
- Singh, V., Gu, N. (2012). Towards an integrated generative design framework. *Design Studies*, 33 (2), pp. 185-207.
- Zimmerman, L., Chen, T., Shea, K. (2017). Generative Shape Design Using 3D Spatial Grammars, Simulation and Optimization. In: Gero, J. (ed) *7th International Conference on Design Computing and Cognition*. Northwestern University, Evanston, Illinois, USA, 27-29 June, 2016.